REMARKS

The applicant thanks the examiner, Mr. Juan C. Ochoa, for having a telephone interview with the inventor, Dr. Richard Mansfield, and the applicant's representatives, David Feigenbaum and Yina Mo, on July 8, 2010. During the interview, independent claims 1, 31, and 34, and references Bounsaythip and Bloom were discussed. The comments of the applicant below are each preceded by related comments of the examiner (in small, bold type).

> **Claims 1, 3-5, 11, 13, 16, 26-28, 30, 31, 33, 34, and 36-40 are rejected under 35 U.S.C. 103(a) as being unpatentable over Bounsaythip et al., (Bounsaythip hereinafter), Overview of Data Mining for Customer Behavior Modeling, (see IDS dated 10/20/08), taken in view of Bloom et al., (Bloom hereinafter), U.S. Pre-Grant publication 8.**
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> **While Bounsaythip discloses "New fields can be generated through combinations, e.g. frequencies, cross-tabulations, averages and minimum/maximum values, relationships between different profiling variables etc ..." (see page 6, # 2.3.3, next to last paragraph); Bounsaythip fails to expressly disclose cross products of at least two variables, each being from the first population of predictor variables, cross products of at least two variables, at least one of the variables being from the pool of predictor variables and having less than the first predetermined level of significance, and automatically selecting a model generation method from a set of available model generation methods to match characteristics of the historical data.**
>
> **Such features are however well-known in the art. For example, Bloom discloses to include cross products of at least two variables, each being from the first population of predictor variables and to include cross products of at least two variables, at least one of the variables being from the pool of predictor variables and having less than the first predetermined level of significance (see paragraphs [0133-9]) and automatically selecting a model generation method from a set of available model generation methods to match characteristics of the historical data (see paragraphs [0003,0007]).**
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> **... it would have been obvious to one of ordinary skill in this art at the time of invention by applicant to utilize the cross products of Bloom in the method of Bounsaythip because Bloom's "Model Seeker"....**

Regarding independent claim 1, neither Bounsaythip nor Bloom described or would have made obvious the second population of predictor variables being extended "<u>to include cross products of at least two variables, at least one of the variables for at least one of the cross products being from the pool of potential predictor variables ... and having less than the first predetermined level of significance</u>," as recited by amended claim 1.

Neither Bounsaythip nor Bloom described or would have made obvious "cross products of at least two variables" to be included in a "second population of predictor variables."

Although the array in paragraph [0142] of Bloom is a cross product of the arrays in paragraph [0141], these arrays are model setting arrays that contained model setting parameters (paragraphs [0098] and [0099]), not predictor variables. The parameters in the array of paragraph [0142] were not included in a "second population of predictor variables," and the parameters in the arrays of paragraph [0141] were not variables from "the pool of potential predictor variables." Bloom stated (emphasis added):

> [0098] In step 204, the model settings arrays 304 are generated. <u>Model seeker 120 builds a plurality of models using different combinations of model settings parameters</u>. For example, Model seeker 120 can build models of different types, such as Nave Bayes, Adaptive Bayes Network, etc. <u>Model seeker 120 can build multiple models of the same type, but with varying model settings parameters, such as model building algorithm parameters</u>. Likewise, <u>Model seeker 120 can build models of different types and multiple models of each type</u>. In order to provide these model building combinations, the parameters included in the MFS and/or the MAS are varied in different combinations. Arrays 304 are generated to store the various combinations of model settings parameters. Arrays 304 provide a plurality of combinations of values for some of the corresponding single model settings attributes. For example, <u>for NaiveBayes models, two arrays are provided: one for the SingleThreshold property and one for the PairwiseThreshold property.</u> The values in the two arrays for NaiveBayes are combined to create multiple pairs of values, one pair for each model to be built. <u>For AdaptiveBayesNetwork models, an array is provided only for the MaximumNetworkFeatureDepth property</u>. An AdaptiveBayesNetwork model is built for each value in the array.
>
> [0099] In step 206, processing is performed <u>for each model settings combination stored in the array or arrays</u> generated in step 206. This processing includes steps 208 and 210. In step 208, a model, which is one of built models 306, is built for a particular model settings combination stored in the array or arrays generated in step 206. ....

Claim 1 also recites that at least one of the variables for at least one of those cross products has "less than the first predetermined level of significance." Because claim 1 earlier recites "selecting variables having at least a first predetermined level of significance from a pool of potential predictor variables ... to form a first population of predictor variables," the at least one variable for at least one of the cross products is from a group of variables that were not selected in the initial pool of potential predictor variables. Neither Bounsaythip nor Bloom described or would have made obvious "at least one of the variables having less than the first predetermined level of significance."

> **As to claim 31, Bounsaythip discloses a machine-based method comprising in connection with a project, generating a predictive model based on the historical data (see page 7, # 2.4), and displaying to a user a lift chart, monotonicity, and concordance scores**

associated with each step in a step-wise model fitting process (see page 40-42, # 7; page 47). Bloom discloses automatically selecting a model generation method from a set of available model generation methods to match characteristics of the historical data about a system being modeled (see paragraphs [0003,0007]).

Regarding independent claim 31, neither Bounsaythip nor Bloom described or would have made obvious "automatically selecting a model generation method from a set of available model generation methods to match characteristics of the historical data." For example, "an automatic machine-based method" (contrary to a manual process) can be used "to select the class of models most suitable to the pool of predictor variables for the associated dataset", as stated in the specification, page 2, lines 6-8.

Bloom automatically generated data mining models (paragraph [0006]). But, instead of "selecting a model generation method from a set of available model generation methods to match characteristics of the historical data," Bloom generated multiple data mining models using the same source data and evaluated the multiple models to select a best model (paragraphs [0006] and [0095]). Bloom stated (emphasis added):

> [0006] .... Model Seeker allows the user or application to conveniently specify parameters for an execution that will asynchronously build multiple data mining models, such as classification models, optionally using multiple algorithms, by systematically varying the algorithm parameters, and then will evaluate and select a "best" model. ....
>
> [0095] The basic approach is to have the user/application input parameters that can be used to define a collection of models to be built and evaluated. Each build is performed using the same source data table or view, and each model is tested using the same second source data table or view. The number of models in the collection may become quite large. Each collection results in one "best" supervised categorical learning model being stored together with its evaluation results. All models except for the best model are deleted. The test results for all models built are retained. The choice of which model is "best" is based on a weighted sum of the percent correct of positive cases and the percent correct of all other cases treated as a single negative case.

As to claim 34, Bounsaythip discloses a machine-based method comprising receiving from separate sources, sets of potential predictor variables representing historical data and dependent variables representing response propensities about a system being modeled (see page 6, # 2.3.2, 2.3.3; page 7, # 2.4), and combine at least two models based on response propensities of each model in order to create cross-modal deciles and based on data weaving of the historical data to provide cross-modal optimization, the combining including concatenating the predictions of the two models (see page 7, # 2.4; page 39, # 4.6). Bloom discloses enabling a user of a model generation tool to combine at least two models (see paragraphs [0006, 0133-9], especially paragraphs [0137, 8])

Regarding independent claim 34, neither Bounsaythip nor Bloom described or would have made obvious "enabling a user ... to combine at least two models ..., the combining including concatenating the predictions of the two models," as recited by claim 34. Bounsaythip described only generating models based on collected data but not combining models. Section 4.6 of Bounsaythip described gathering and analyzing data collected from web transaction logs for generating a "rule" for future marketing strategies (page 39, last paragraph, and page 41, paragraphs below Table 18). As indicated by the title of the section 4.6.1, what was being clustered was data, not models (page 39).

For example, on pages 41-42, Bounsaythip showed in Table 17 recorded data about 5 visitors visiting different types of webpages "planning", "fashion & beauty", "food & venue", "travel", and "gifts". Table 18 is generated by clustering and reorganizing the data of Table 17. From Table 18, "associations rules" can be found by directly reading the contents of the table (in other words, rewriting the numerical contents of the table into words). For example, Table 18 shows that there are 3 visitors who visited both the planning and the fashion & beauty webpages, which is higher than any other combinations of two different webpages. Analysis of this data led to a conditioned (e.g., if one visits fashion & beauty, then ...) rule in which the user is interested (page 41).

Bounsaythip generated rules using the clustered data in Table 18, by including different conditions or different variables. Bounsaythip's combination of data or variables for generating the rules was not "combining at least two models", at least because Bounsaythip did not have models generated for combination, but only had clustered data for generating the rules.

Bloom also did not describe and would not have made obvious "to combine at least two models ..., the combining including concatenating the predictions of the two models." Although Bloom referred to "a combination of ... models" in paragraphs [0086], [0098], [0115] and [0137]-[0138], the term "a combination of" here meant "a group of", not "combining". Bloom did not "combine at least two models," but generated a group of models of the same type or different types based on different model setting parameters (paragraph [0086]). Bloom stated (emphasis added):

[0086] Combination model specifications--The information needed to build a single model is contained in an instance of MiningFunctionSettings (MFS) and MiningAlgorithmSettings (MAS). When a combination of models are built of the same type by Model Seeker, the only specifications that differ from one model to another are the values for the data members of the MAS. To avoid repeating common information for many MAS instances, Model Seeker introduces several new subclasses of MAS. In particular, the classes CombinationNaiveBayesSettings and CombinationAdaptiveBayesNetwork- Settings allow for an array of values for some of the corresponding single model settings attributes. For NaiveBayes models, two arrays are provided: one for the SingleThreshold property and one for the PairwiseThreshold property. The values in the two arrays for NaiveBayes are combined to create multiple pairs of values, one pair for each model to be built. For AdaptiveBayesNetwork models, an array is provided only for the MaximumNetworkFeatureDepth property. An AdaptiveBayesNetwork model is built for each value in the array.

[0098] In step 204, the model settings arrays 304 are generated. Model seeker 120 builds a plurality of models using different combinations of model settings parameters. For example, Model seeker 120 can build models of different types, such as Nave Bayes, Adaptive Bayes Network, etc. Model seeker 120 can build multiple models of the same type, but with varying model settings parameters, such as model building algorithm parameters. Likewise, Model seeker 120 can build models of different types and multiple models of each type.

[0115] 7. The models to be built and evaluated can be a combination of Naive Bayes (NB) and Adaptive Bayes Network (ABN) models. The user may include a combination of as many NaiveBayesAlgorithmnSettings, CombinationNaiveBayesSettings (CNBS), AdaptiveBayesNetworkAlgorithmSettin- gs, and CombinationAdaptiveBayesNetSettings (CABNS) instances in the specification as desired.

[0116] 8. The ModelSeekerResult information for each model includes the following: ....

Claims 2, 6-10, 14, 15, 17, 18, and 32 are rejected under 35 U.S.C. 103(a) as being unpatentable over Bounsaythip taken in view of Bloom as applied to claims 1 and 31 above, and further in view of Karen Papierniak, (Papierniak hereinafter), Pre-Grant publication 20030154442.

Claims 23, 25, 29, and 35 are rejected under 35 U.S.C. 103(a) as being unpatentable over Bounsaythip taken in view of Bloom as applied to claims 1 and 34 above, and further in view of Heller et al., (Heller hereinafter), U.S. Patent 7,349,827.

All of the dependent claims are patentable for at least similar reasons as those for the claims on which they depend are patentable.

Canceled claims, if any, have been canceled without prejudice or disclaimer.

Any circumstance in which the applicant has (a) addressed certain comments of the examiner does not mean that the applicant concedes other comments of the examiner, (b) made arguments for the patentability of some claims does not mean that there are not other good reasons for patentability of those claims and other claims, or (c) amended or canceled a claim

does not mean that the applicant concedes any of the examiner's positions with respect to that claim or other claims.

Please apply $245 for the Petition for Extension of Time fee and any other charges or credits to deposit account 06-1050, referencing attorney docket 17146-0007001.

Respectfully submitted,

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